https://doi.org/10.5755/j02.eie.44803 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, EARLY ACCESS

Signal Processing and Fault Diagnosis on Structure Vibration Measurement using a New Composed Deep Learning Model

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***Abstract*—To protect offshore jacket platforms, it is essential to carry out the structure fault diagnosis. This paper proposes a new approach for identifying the structure faults in offshore jacket platforms, which is based on the integration of the structural vibration data, a sophisticated data fusion process, and an intelligent diagnosis algorithm. In this new approach, firstly, the temporal convolutional network (TCN) is adopted to solve the efficiency bottleneck of the traditional recurrent neural networks in long time series signals, and significantly enhances the ability to capture long-distance dependent features in the structural response signals through the introduction of a dilated convolutional structure. Secondly, the bidirectional gated recurrent unit (BiGRU) network fuses forward and reverse gated recurrent units, which can effectively capture the forward and backward correlated timing features in the structure vibration data. The Attention mechanism then further weights and optimises the BiGRU timing outputs so that the model can automatically focus on the signal pattern that is most discriminative for the fault identification. Furthermore, the Artificial Lemming Algorithm (ALA) is used to optimise the hyperparameters of the TCN and BiGRU to improves the model efficiency and avoid the local optimum during the model training, thereby enhancing the generalisation performance of the proposed model. The validity of the proposed ALA-TCN-BiGRU model is substantiated through simulation and experimental validation. The results indicate that the proposed model can achieve an overall detection accuracy of over 98% for the jacket structure, which is superior to several popular diagnosis methods, thus demonstrating its efficacy in signal processing and fault diagnosis of the offshore jacket platforms.**

***Index Terms*—Signal processing; Deep learning; Structure health monitoring; Fault detection**

I. INTRODUCTION

As the primary support structures for offshore oil and gas extraction and wind power generation facilities, the jacket platforms suffer from waves, wind loads and corrosion over extended periods, making them susceptible to fatigue cracks, material degradation, joint failure, and other forms of damage [1]. Failure to detect these damages in a timely manner poses a risk of structural failure or even platform collapse, which could lead to major safety incidents and environmental pollution [2].

With the continuous expansion of global marine energy development, the number of offshore platforms and their service lifespans are steadily increasing, making Structural Health Monitoring (SHM) increasingly critical. The structural modal parameters, including the natural frequencies, vibration modes and damping ratios, are widely used for SHM [3]. However, the combined effects of extreme marine environments still limit the effectiveness of existing technologies in practical applications, creating an urgent need to develop more advanced and reliable intelligent diagnostic methods.

Traditional inspection methods can be broadly categorized into manual inspection, periodic inspection, vibration monitoring, and strain monitoring. Among these, manual and periodic inspections offer the advantages of being intuitive and reliable, making them suitable for identifying localized damage. However, they are inefficient, costly, and struggle to cover concealed areas; vibration monitoring and strain monitoring, on the other hand, offer the advantage of automated monitoring and are suitable for overall performance assessment. However, they lack sufficient sensitivity to detect early-stage, minor damage and require the deployment of a large number of sensors. Therefore, it is necessary to extract useful information from these signals to realise the identification of underlying structural damages [4].

Although existing technologies have demonstrated their reliability in laboratory environments, the combined effects of extreme marine environments still limit their effectiveness in practical applications. Recently, the deep learning has achieved promising accomplishments in many fields [5]. Furthermore, it has established a novel technical paradigm for damage identification tasks on offshore pipeline installation platforms. The application of deep learning algorithms in engineering signal processing has brought significant technical advantages, as evidenced by the development of innovative applications [6].

This study employs finite element analysis (FEA) and deep learning (DL) technologies for the fault monitoring of offshore structures. We propose an ALA-TCN-BiGRU-Attention model, which utilizes ALA intelligent optimization to identify the optimal hyperparameters for the BiGRU. This approach not only avoids complex, time-consuming, and labor-intensive manual parameter tuning but also enhances the model's convergence speed and generalization capability. This novel method offers dual advantages: First, FEA provides physical law constraints for the collected data; second, DL enhances the ability to learn the nonlinear relationship between the data and defect patterns. The combination of these two technologies will improve the identification accuracy.

The stress and strain distributions of the structure were calculated through numerical simulations. Using the ALA-TCN-BiGRU-Attention model, damage features can be automatically extracted from structural dynamic response data, thereby enabling the intelligent classification of cracks, corrosion, and other defects. Subsequent experimental results demonstrate that the new method can detect the structural damages with an average accuracy exceeding 98%, outperforming traditional mainstream methods by 9.5 percentage points. Furthermore, analysis indicates that ALA enhances multi-scale feature extraction efficiency by 50% through optimized collaborative training of TCN's extended convolutional kernels and BiGRU's gating parameters; meanwhile, the attention mechanism effectively focuses on damage-sensitive feature regions via dynamic weight allocation. Therefore, this study provides a new generation of intelligent diagnostic tools for offshore SHM.

The structure of this paper is as follows: Section 2 proposes the new method; Section 3 establishes a model of an offshore jacket platform; Section 4 presents experimental validation; and Section 5 summarizes the research results.

II. RELATED WORKS

This section provides a systematic review of relevant research in the field of structural damage identification for offshore platforms, covering traditional methods based on modal parameters, machine learning and deep learning methods, hybrid neural network architectures, as well as the latest advancements in attention mechanisms and intelligent optimization algorithms.

A. *Modal Detection Method*

Shokrgozar et al. [7] utilized the directional spectral decomposition method to extract the axial and lateral damage indices for structure damage localization. Zhao et al. [8] proposed a new cross-modal modal strain energy index to reduce the impact of environmental noise on the accuracy of damage localization. Khosravan et al. [9] proposed an improved modal strain energy decomposition method (IMSEDM) to decompose modal strain energy into axial and bending strain energy. This method utilizes modal frequencies, modal shapes, and the aforementioned four features to locate damaged components. Nejad et al. [10] used the Discrete Wavelet Transform (DWT) to locate the damages in pipeline casing structures. By applying the DWT to acceleration signals before and after the structural damage, they obtained the wavelet coefficients and the associated modal function for the damage detection.

Although the aforementioned methods based on modal parameters have demonstrated good damage localization capabilities under laboratory conditions, they face numerous challenges in practical marine engineering applications: issues such as severe noise interference from the marine environment, limited sensor deployment, and the difficulty of detecting early-stage minor damage constrain the engineering practicality of these methods.

B. *Machine Learning and Deep Learning Detection*

Rong et al. [11] used the Extreme Learning Machine (ELM) to detect the structure damages. Miche et al. [12] proposed an improved P-ELM algorithm, extending its application beyond classification problems to include regression problems. However, it should be noted that these algorithms do not address the fundamental challenge inherent in neural network frameworks, namely the need for lengthy iterations. Azimi et al. [13] employed the Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) for SHM. Bao et al. [14] adopted the one-dimensional convolutional neural network (CNN) to detect the structural damages in offshore pipeline. By integrating stochastic dimension reduction techniques with deep learning algorithms, this method achieves high-precision detection of structural damage in complex marine environments. Cho et al. [15] used the Long Short-Term Memory (LSTM) to analyse the long-term dependencies in time-series vibration data. Compared to traditional Recurrent Neural Networks (RNNs), the LSTMs have effectively addressed issues such as the gradient vanishing and information forgetting. The Gated Recurrent Unit (GRU) is another type of RNN network that can be applied to a wide range of applications, including but not limited to the handwriting recognition and natural language processing [16]. Many researchers have compared the GRUs with the LSTMs [17-19] and found that the GRUs are easier to train, with learning performance that rivals or even surpasses that of the LSTMs in many applications.

Notably, Yan et al. [20] performed the damage detection in offshore jacket platforms. This study proposed a novel hybrid deep learning network model that combines a Time-Convolutional Network (TCN) with a Bidirectional Long Short-Term Memory (BiLSTM) network. Experimental results show that the proposed model achieves an average damage identification accuracy of 99%, surpassing existing deep learning methods, and holds broad application prospects in the field of offshore SHM. Furthermore, Djordjevic et al. [21] proposed a fault detection method based on Endocrine CNN. The results indicate that the Endocrine CNN performs optimally in time series classification tasks and has the potential for widespread application in industrial predictive maintenance, which provides new insights into vibration-signal-driven structural fault diagnosis.

C. *Hybrid Neural Network Architectures*

Hybrid neural network architectures have achieved breakthroughs in feature modeling, multimodal tasks, computational efficiency, and scalability by integrating the strengths of different algorithms, thereby significantly enhancing the performance, adaptability, and interpretability of AI systems. Wang et al. [22] developed a CNN-BiLSTM model that utilizes the BiLSTM to process the time-series information to fully integrating temporal context; this model innovatively integrates a squeeze-excite (SE) attention mechanism to intelligently filter features extracted by the CNN. Li et al. [23] proposed a Bayesian optimization to address the shortcomings of traditional linear models in capturing sea-level changes. Liang et al. [24] utilized the PSO to improve the detection accuracy and model generalization.

Liu et al. [25] proposed a method combining the Least Squares Support Vector Machines (LSSVM) with the Northern Gyrfalcon Optimization (NGO) to establish a mapping relationship between the magnetic field gradients and changes in apparent resistivity. Guo et al. [26] proposed an improved ELM model for the identification and classification of the wear state of ordered grinding wheels. Mezina et al. [27] found that the TCN-LSTM and a U-Net model can provide higher accuracy in traffic flow classification. It is evident that hybrid neural network architectures, by integrating the strengths of different algorithms, have achieved breakthroughs in feature modeling, multimodal tasks, computational efficiency, and scalability, thereby significantly enhancing the performance, adaptability, and interpretability of AI systems.

D. *Attention Mechanisms and Optimization Algorithms*

Attention mechanisms have long been a focus of extensive research [28][29][30], as they prioritize key features by dynamically allocating weights. Studies have shown that this approach can improve the performance and interpretability of deep learning models in natural language processing, computer vision, and multimodal tasks [31][32]. Human vision focuses on key information through the fovea and suppresses peripheral details to optimize cognitive resources. Inspired by this, artificial intelligence employs attention mechanisms to dynamically allocate computational weights, thereby improving information processing efficiency.

Although meta-heuristic algorithms (such as genetic algorithms and particle swarm optimization) perform well in complex optimization problems, they still suffer from critical shortcomings, including a tendency to get stuck in local optima, an imbalance between exploration and exploitation, a sharp drop in performance in high-dimensional spaces, and poor adaptability to dynamic environments. Improvements are therefore needed to enhance their robustness and adaptability. To address this need, the Artificial Lemming Algorithm (ALA) [33] was proposed based on meta-heuristics. This algorithm has demonstrated exceptional solution accuracy, convergence speed, and stability in most test cases. However, a single intelligent algorithm is clearly insufficient for handling diverse tasks.

Compared to traditional methods that rely on manually preset modal parameters (such as frequency and vibration modes), deep learning, through an end-to-end learning paradigm, can directly extract high-order abstract features from structural dynamic response signals (such as time-series data of acceleration, velocity, and displacement), thereby effectively capturing subtle damage-sensitive information that is difficult for traditional algorithms to identify [34]. Jia et al. [35] investigated the application of time-domain convolutional networks (TCNs) based on time-domain attention mechanisms in gas concentration prediction, further validating the broad applicability of TCNs combined with attention mechanisms in the field of time-series signal processing.

III. PROPOSED NEW DETECTION METHOD

After considering the need for robust extraction of features from long time series in complex environments and the accuracy of damage recognition, we constructed a feature extraction backbone network based on TCN (Temporal Convolutional Network) and BiGRU (Bi-directional Gated Recurrent Unit). To further enhance the recognition of key features, we introduce an Attention mechanism (Attention), which dynamically assigns weights to the feature vectors output from TCN and BiGRU, focusing on the most discriminative pieces of information for damage recognition. Considering the sensitivity of the model performance to hyperparameters, the ALA algorithm is used to globally optimize the key hyperparameters of the fusion model to determine the optimal configuration. The optimized model will be trained and validated by receiving long time series signals from the simulation model and the experimental model, respectively.

The implementation of the proposed integration model is depicted in Fig. 1.

(1) Data acquisition: the solid edge software is used to establish the structure finite element (FE) model, and the ANSYS software is used to analyse the FE model to generate the vibration data of the structure under health and damage conditions, respectively.

(2) TCN: the TCN is used to extract the time-series features from the vibration data through causal and inflationary convolution.

(3) BiGRU-Attention: the BiGRU module captures long-range dependencies and generates enhanced feature sequences containing rich contextual information through the front and back GRUs, while constructing a relationship between the features and damages. The attention is used to select the most informative features.

(4) ALA: There are multiple hyperparameters in the training process of the proposed integrated deep learning model, and these hyperparameters are optimized with ALA to reduce the tedious tuning process.

In addition, training is performed using the Adam optimizer, the initial learning rate and L2 regularization coefficients are also optimized by ALA, the maximum number of training rounds is 500, and the learning rate decreasing strategy is piecewise.

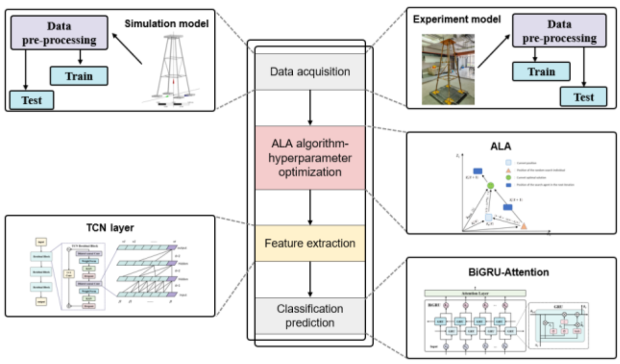


Fig. 1. Overview of the proposed method.

A. *Data Acquisition*

Simulation and experiment are the two core means of data acquisition. In simulation, the model of the offshore wind turbine duct frame was firstly constructed by the Solid Edge, and then imported into the ANSYS software for simulation analysis. The modulus of elasticity of the defective components was set to simulate different damage conditions, so as to obtain the acceleration response signals under different damage conditions. In terms of experiments, a test bench was built in the laboratory as the simulation model, and the structural damage was applied to the prototype by reducing the cross-sectional area of the defective elements, and a vibrator was applied to the test bench to simulate the action of waves, currents, and winds in the marine environment, and acceleration sensors were installed at key nodes of the test bench to collect the structural vibration, so as to obtain the acceleration vibration response signals of the structure.

In data preprocessing, the vibration signal data is segmented using the overlap segmentation method to maximize the utilization of the data, and then the data is normalized using the Min-Max normalization operation according to Eq. (1).

$$X_n = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where X_n is the normalized data, x is the original data, x_{min} and x_{max} are respectively the minimum and maximum values of x. Normalization ensures that the data are at the same scale, avoids model bias due to feature scale inconsistency, and makes the influence of each feature on the model more balanced, thus improving the model fitting effect and generalization ability.

After normalizing the data, the normalized data will be converted from a matrix to an array of cells to feed the deep learning model.

B. *Establishment of TCN*

The TCN design used in this study consists of three main components: the causal convolution, the inflationary convolution and the residual linking [32]. The causal convolution ensures that the current output of the model is based exclusively on current and past information. This is achieved by preventing the leakage of future data.

For a t-element input sequence

$$x = \{x_1, x_2, \ldots, x_t\} \tag{2}$$

The causal convolution definition equation is described in Eq. (3).

$$y_t = (x * f)(t) = \sum_{i=0}^{k-1} f(i) \cdot x_{t-i} \tag{3}$$

where f is a convolution kernel with size k; y_{t-i} denotes the convolution output.

Dilated convolution effectively expands the sensory field of the network by increasing the spacing between the convolution kernels, helping the model to capture long time-distance dependencies in sequential data. The dilated convolution is defined as follows.

$$y_t = (x *_d f)(t) = \sum_{i=0}^{k-1} f(i) \cdot x_{t-d \cdot i} \tag{4}$$

where d is the dilation factor, which controls the dilation interval of the convolution kernel. The d in this study is set adaptively, and for each TCN block, the expansion factor is randomly generated between 1 and maxDilation. maxDilation's value is adaptively calculated based on the total number of input samples. This randomization and adaptive strategy is designed to allow the network to capture features at different time scales.

The residual connection structure, on the other hand, effectively mitigates the gradient vanishing problem during the deep network training process and enhances the training stability and generalisation ability.

The working schematic of this TCN is given in Fig. 2 and consists of three consecutive residual blocks with convolution kernel size 4 and 45 convolution kernels. The vibration signal is first fed into the first residual block, which undergoes a convolution operation in the first convolutional layer (Conv1) to generate the first layer of features, which is immediately followed by layer normalization for stabilizing the training process. Then a Dropout with a value of 0.02 is attached to regularize the network and reduce the risk of overfitting.

The first layer of features is then input to the second convolutional layer (Conv2) to reduce the feature size to generate the second layer of features, and after layer normalization again, the resulting features are corrected using the activation function KAN, which is given as

$$Z = \tanh(W \cdot X + B) \tag{5}$$

where W and B are learnable parameters for each convolutional kernel, initialized to random values and zero vectors, corresponding to 45 convolutional kernels, respectively. Subsequently a Dropout is again picked up to regularize the network. A 1x1 convolution layer is used for the dimensionality reduction to ensure the consistency between the input and output.

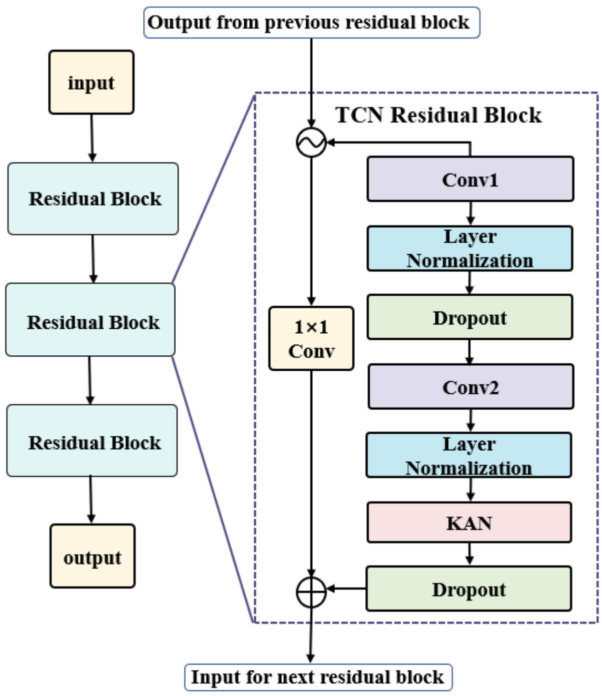


Fig. 2. TCN module.

C. BiGRU-Attention Model

The BiGRU is an improved recurrent neural network structure developed on the basis of GRU, which consists of a forward GRU and an inverse GRU, and its main advantage is that it simultaneously captures the dependencies between the front and back time steps in a data sequence [33].

The GRU itself controls the information flow through the update gate and reset gate. The update gate is expressed as

$$z_t^{\rightarrow} = \sigma(W_z x_t + U_z h_{t-1}^{\rightarrow} + b_z) \quad (6)$$

where W_z is the weight matrix of the input to the update gate, U_z is the weight matrix of the hidden state to the update gate, b_z is the bias term of the update gate, and σ is the sigmoid activation function.

The reset gate is described as

$$r_t^{\rightarrow} = \sigma(W_r x_t + U_r h_{t-1}^{\rightarrow} + b_r) \quad (7)$$

where, W_r is the weight matrix of the input to the reset gate, U_r is the weight matrix of the hidden state to the reset gate, and b_r is the bias term of the reset gate.

The candidate hidden state is defined by Eq. (8).

$$\tilde{h}_t^{\rightarrow} = \tanh\,(W_h x_t + U_h(r_t^{\rightarrow} \cdot h_{t-1}^{\rightarrow}) + b_h) \quad (8)$$

where W_h is the weight matrix of the input to the candidate hidden state, U_h is the weight matrix of the hidden state to the candidate hidden state, and b_h is the bias term of the candidate hidden state.

The update memory $h_t^{\rightarrow}$ is defined by Eq. (9).

$$h_t^{\rightarrow} = (1 - z_t^{\rightarrow}) \cdot h_{t-1}^{\rightarrow} + z_t^{\rightarrow} \cdot \tilde{h}_t^{\rightarrow} \quad (9)$$

Eq. (9) indicates that the new hidden state is obtained by a linear combination of the previous hidden state moment and the current candidate hidden state according to the update gate.

The forward GRU is to produce a hidden sequence $\overrightarrow{h_t}$ while the backward GRU is to generate a reverse sequence $\overleftarrow{h_t}$. In each time step, the BiGRU splices the forward and backward hidden states to obtain the hidden state as

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \quad (10)$$

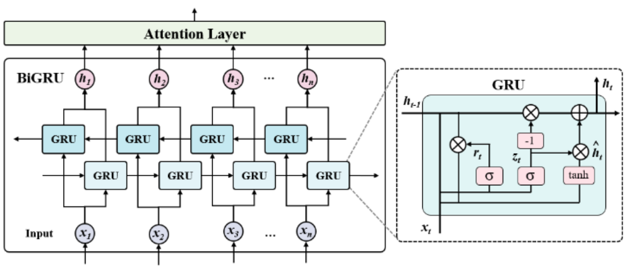


Fig. 3. BiGRU-Attention architecture.

In addition, the attention mechanism is a component of the neural network that mimics the human visual focusing ability and is able to weight the feature information according to the importance of different time steps, where a very small weight value is assigned to useless information and a large weight value is assigned to important information. The network architecture of BiGRU-Attention is shown in Fig. 3.

In this study, the feature sequences extracted by TCN are flattened and fed into the BiGRU network. BiGRU scans the feature sequences in both the front and back directions to capture the long range dependencies and generate enhanced feature sequences that contain rich contextual information. Among them, the hyper-parameters of the BiGRU are optimised by the ALA. The outputs of the BiGRU, the sequences fusing bi-directional contextual information, are finally fed into the self-attention layer, which is configured to use 1 attention head (HEAD).

D. ALA Optimisation

The ALA is a novel bionic meta-heuristic optimisation algorithm inspired by the four typical behaviours of lemmings: long-distance migration, burrowing, foraging, and hiding from predators. The ALA achieves a dynamic balance between global search and local exploitation by constructing corresponding mathematical models, and is particularly suitable for dealing with high-dimensional, non-convex and non-linear optimisation problems.

The long-distance migration and burrowing behaviours in the ALA are used for global exploration, simulating the lemming's wide-range movement and tunnel construction in search of better habitats and resources; while the foraging and predator evasion behaviours reflect the local exploitation strategy, which allows the individual to explore the potential optimum near the existing high-quality solutions. To control the behavioural choices of the algorithm at different stages, the ALA introduces an energy decreasing mechanism. In addition, the ALA integrates Brownian motion and Lévy flight mechanisms to enhance the local jumping ability through high-frequency fine-tuning, and use the heavy-tailed distributions to expand the global search range to avoid local optima. More details of the ALA can refer to [26]. Fig. 4 shows the ALA architecture.

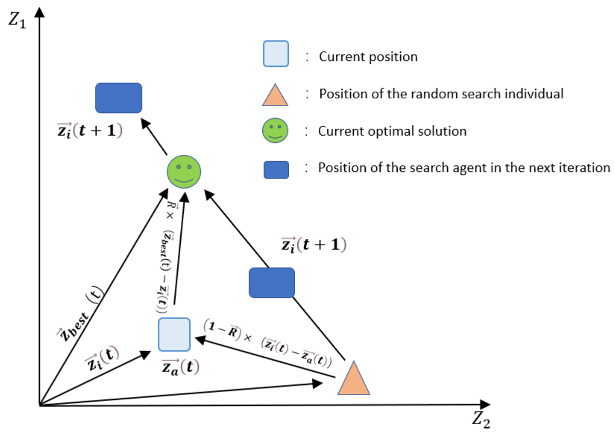


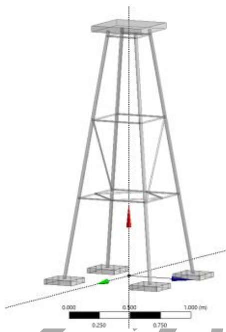
Fig. 4. ALA module.

In this study, we propose the ALA-TCN-BiGRU-attention model for structural vibration data, in which the role of ALA as an optimizer focuses on optimizing the learning rate, the number of GRU hidden units, and the L2 regularization coefficients, which indirectly affect the training process and performance of the TCN and attention layers. Due to the holistic nature of the model, the optimization of ALA may indirectly support the TCN and attention mechanisms by improving the training efficiency and generalization ability, but its direct optimization goal is limited to hyperparameters rather than architectural details.

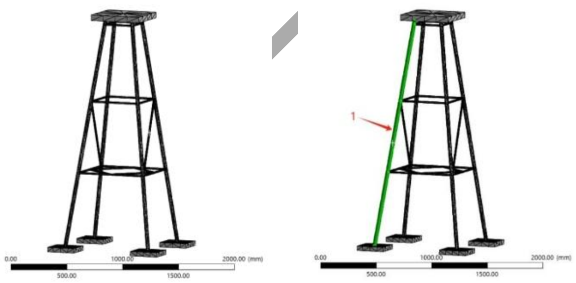
IV. FINITE ELEMENT SIMULATION

A. *Finite Element Model*

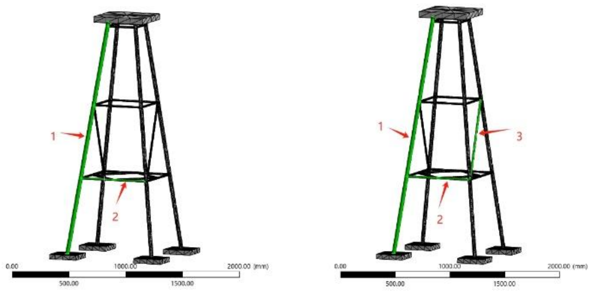
A model of the offshore jacket platform was constructed using Solid Edge software (see Fig. 5) and then imported into ANSYS software for finite element analysis. The platform is about 2 m high, and structural steel was selected as the material for the whole structure with the following material properties: density, 7850 kg/m3; Poisson's ratio, 0.3; and Young modulus, 306 GPa. In this study, the damage of the Offshore Jacket Platforms in the marine environment was simulated by decreasing the modulus of elasticity of the unit rods. Four damage modes (i.e., no damage, single damage, double damages, and multiple damages) were designed. The damage locations were set at different levels of the rods, such as main flange beam, transverse flange beam and diagonal flange beam. Without loss of generality, a transient dynamic analysis was carried out in ANSYS with a time step of 0.02s by applying an instantaneous impact force of 10,000N on the side of the upper plate. The distribution of damage is illustrated in Fig. 5. The detailed damage conditions are enumerated in Table 1.



(a)



(b) (c)



(d) (e)

Fig. 5. Simulation model. (a) Solid Edge model; (b) Normal model; (c) single damage model; (d) double damage model; (e) multiple damage model.

TABLE I. SIMULATION CONDITIONS.

Damage Condition	Damage location	Outside diameter of replace rod
Normal	0	0
Single-damage	1	50%
Double-damdge	1, 2	50%, 40%
Multiple-damage	1, 2, 3	50%, 40%, 30%

The objective of this study is to evaluate the acceleration response of offshore jacket platforms under different damage conditions. To this end, the acceleration response characteristics of disparate nodes under varying damage conditions will be systematically investigated by applying an impulse load to the upper top plate of the offshore jacket platform and selecting an acceleration probe at one of the nodes of the main spar. Fig. 6 shows the vibration response of the finite element model for a node of the model under undamaged conditions.

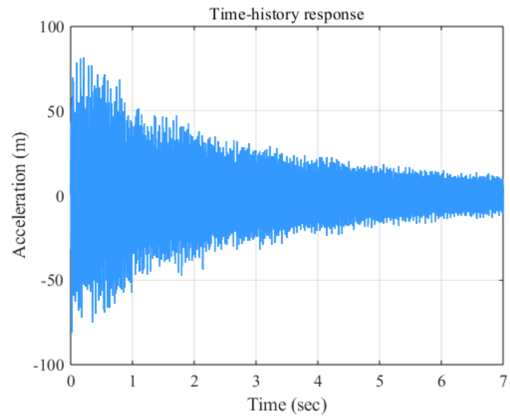


Fig. 6. Vibration response diagram.

B. *Simulation Data Processing*

The model training is conducted on the Windows 11 platform utilising MATLAB2024a.The hardware configuration of the experimental platform comprises an RTX 3060 8G GPU and an Intel Core i7-12700H CPU. The total data set for this finite element simulation consists of 1,600 sets, with 85% allocated to the training set and 15% designated for the test set. The fitness curve of the training process by imputing the simulation vibration data into the proposed ALA-TCN-BiGRU-attention model is demonstrated in Fig. 7.

The ALA algorithm is utilised to automate the optimisation of BiGRU for the optimal number of hidden layer nodes, Best_hd, in addition to the ideal initial learning rate, Best_lr, and the optimal L2 regularisation coefficient, Best_l2. Furthermore, certain parameters of the network are specified, as illustrated in Table 2.

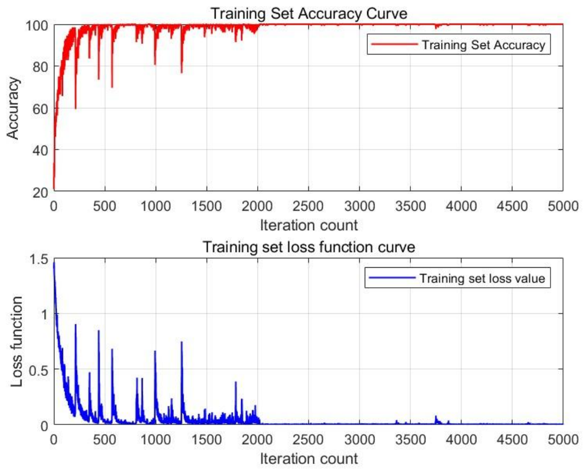
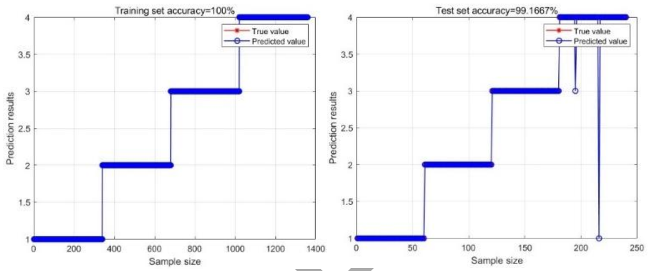


Fig. 10. Training curve using the simulation data.

TABLE II. TRAINING PARAMETER SETTINGS.

Parameter	Value
ALA SearchAgents no	8
ALA Max iteration	5
ALA optimal parameters	3
numFilters	45
filterSize	4
dropoutFactor	0.02
numBlocks	3
Best_hd	14
Best_l2	0.003
Best_lr	0.002

The model is trained based on the appeal parameters, and the training accuracy is demonstrated in Fig. 8, where a 100% was achieved in the training set and 99.17% in the test set.



(a) (b)

Fig. 8. Accuracy: (a) Train data; (b)Test data.

In addition, Fig. 9 shows the confusion matrix, which shows the accuracy of the different locations and severity of damage in the four damage scenarios.

In the confusion matrix, the evaluation metrics include the accuracy, precision, recall and F1 score. In order to validate the model effectiveness, this research partially disassembles the model into modules and create two individual ablation models: (1) TCN; (2) TCN+BiGRU; and the CNN, LSTM, and BiLSTM are taken as comparison baselines. The results are presented in Table 3 and Fig. 10.

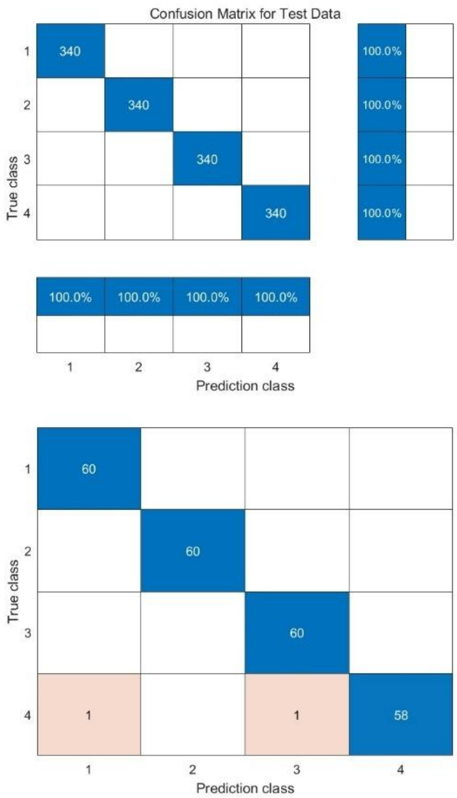


Fig. 9. Confusion matrix: (a) Train data; (b)Test data.

TABLE III. EVALUTION METRICS OF DIFFERENT ALGORITHMS.

Model	Evalution metrics	Values
CNN	Accuracy	0.7780
	Precision	0.7820
	Recall	0.7680
	F1 score	0.7820
LSTM	Accuracy	0.8444
	Precision	0.8444
	Recall	0.8444
	F1 score	0.8444
BiLSTM	Accuracy	0.9206
	Precision	0.9229
	Recall	0.9206
	F1 score	0,9208
TCN	Accuracy	0.9325
	Precision	0.9325
	Recall	0.9325
	F1 score	0.9325
TCN-BiGRU	Accuracy	0.9600
	Precision	0,9600
	Recall	0.9582
	F1 score	0.9582
ALA-TCN-BiGRU-Attention	Accuracy	0.9875
	Precision	0.9881
	Recall	0.9875
	F1 score	0.9876

It can be seen that the detection model proposed in this paper achieves the highest fault diagnosis rate. Furthermore, the model has the capacity to automatically seek optimisation for hyper-parameters, thereby eliminating the necessity for laborious manual parameter tuning. This process enables the achievement of the optimal state in a more efficient manner. Furthermore, the observations suggest that the key features of the structure vibration can be correctly extracted by the proposed model.

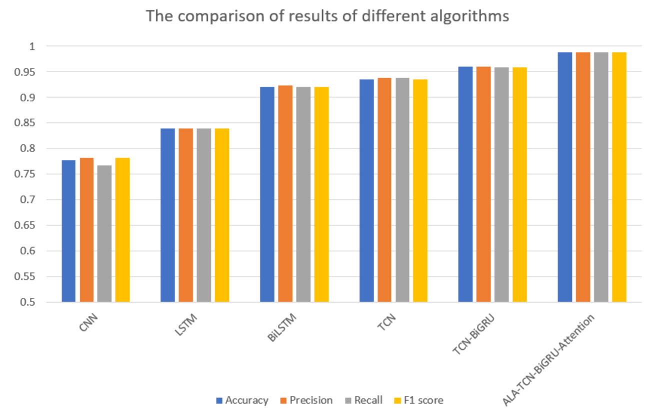
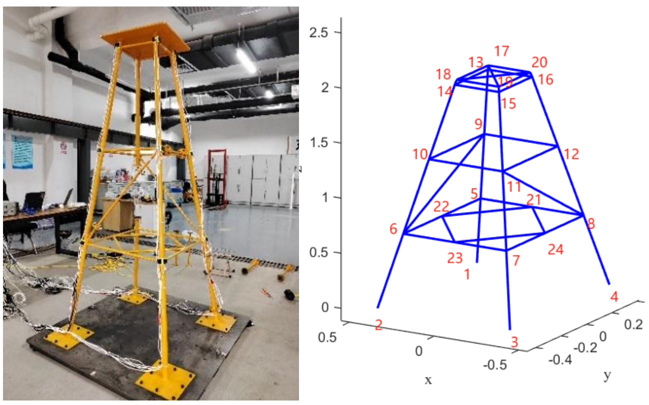


Fig. 10. Results of ablation experiment.

V. Experimental Evaluation

A. Physical Model

With reference to the finite element model, this research builts a similar model of Offshore Jacket Platforms in the laboratory to verify the effectiveness of our proposed algorithm based on the real data collected from the physical object. The physical model and model node information of the Offshore Jacket Platforms are shown in Fig. 11. The Q235 is used to construct the four-layer structure. The width between each layer is respectively 0.39m, 0.30m, 0.22m, and 0.13 m; and the vertical height of each layer is 0.65 m. The inner diameter of the main support is 26.5 mm, and the outer diameter is 32 mm, and the inner diameter of the transverse and diagonal braces of each circular tubing unit is 13.6 mm, and the outer diameter is 16 mm.



(a) (b)

Fig. 11. Physical model and nodal diagram of the physical model

B. Experimental Data Processing

To simulate the environment in the ocean more realistically, this research applied the impact loads on the top plate from the X-axis and Y-axis directions, and set up four damage modes, which corresponding to the damages in the simulation models. The working condition design is shown in Table 4.

The data was collected at a step size of 0.0002 s, with a sample size of 400, resulting in a total time of 0.08 s for the entire process. In order to maximise the utility of the data collected, a sliding window technique was employed for the segmentation of the data. The experiment involved 1,000 groups of data. Of these, 80% were utilised for the training set, while the remaining 20% constituted the test set. The fitness curve of the training is demonstrated in Fig. 12.

TABLE IV. DESIGN FOR DAMAGE CONDITIONS.

Damage Condition	**Outside diameter of replace rod**
Normal	0
Single-damage	21mm
Double-damage	21mm, 21mm
Multiple-damage	21mm, 21mm, 10mm

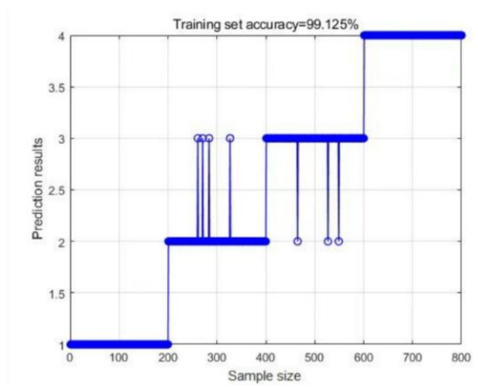
This research uses the ALA algorithm to automatically optimise BiGRU for the best number of hidden layer nodes, Best_hd, as well as for the best initial learning rate, Best_lr, and the best L2 regularisation coefficient, Best_l2. This research also specifies some parameters of the network, as shown in Table 5.

TABLE V. NETWORK PARAMETERS

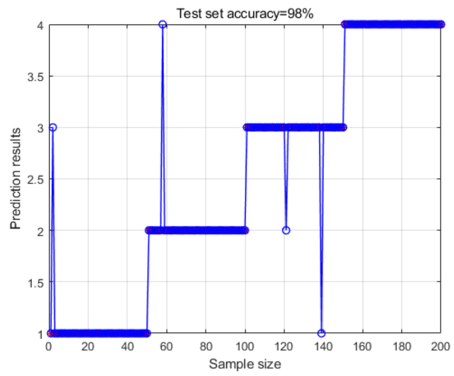
Parameter	**Value**
numFilters	45
filterSize	4
dropoutFactor	0.02
numBlocks	3
Best_hd	46
Best_l2	0.01
Best_lr	0.0043

The model is trained based on the appeal parameters, and the training accuracy is demonstrated in Fig. 12, where a 99.125% was achieved in the training set and 98% in the test set.

In addition, Fig. 13 shows the confusion matrix, which shows the accuracy for different locations and damage severities in the four damage scenarios. Meanwhile, this research calculated four metrics for ALA-TCN-BiGRU-Attention: Accuracy = 98%, Precision = 0.9752, Recall = 0.9752, and F1 Score = 0.9752.In order to highlight the effectiveness of the model, this research gives the results of the CNN, LSTM, BiLSTM, TCN, TCN- BiGRU and ALA-TCN-BiGRU-Attention models for the comparison of identification results. As can be seen from Figure 14 and Table 6, the fused model ALA-TCN-BiGRU-Attention proposed in this study achieves the best performance, and it can be seen that in the damage classification of Offshore Jacket Platforms, compared to using a certain model alone, the combined model has more excellent results in all indicators.

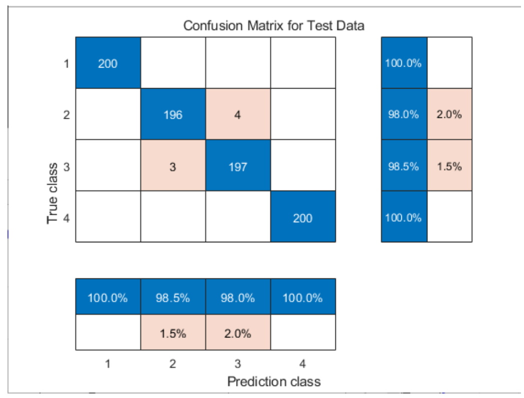


(a)

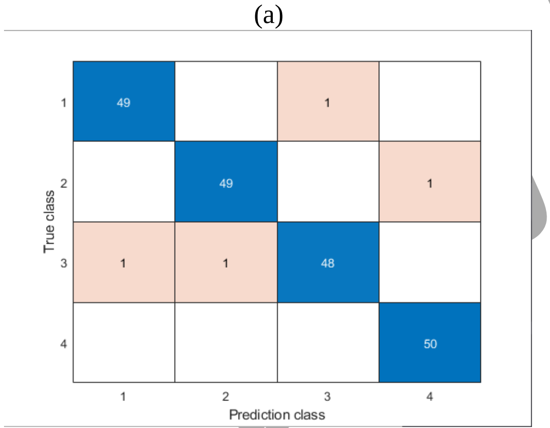


(b)

Fig. 12. Fault detection accuracy: (a) Train data; (b)Test data.



(a)



(b)

Fig. 13. Confusion matrix: (a) Train data; (b)Test data.

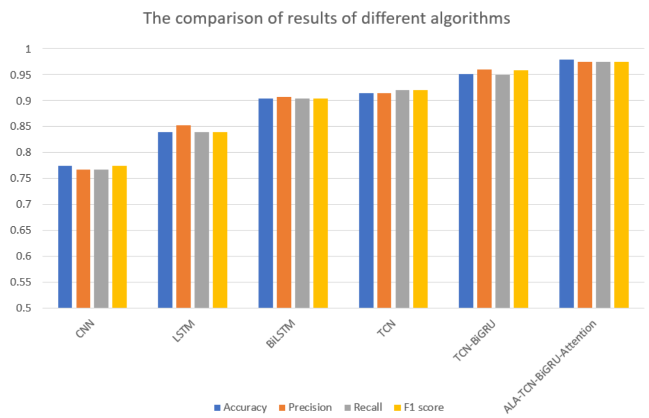


Fig. 14. Results of ablation experiment.

TABLE VI. EVALUTION METRICS OF DIFFERENT ALGORITHMS.

Model	Evalution metrics	Values
CNN	Accuracy	0.7750
	Precision	0.7680
	Recall	0.7680
	F1 score	0.7750
LSTM	Accuracy	0.8400
	Precision	0.8531
	Recall	0.8400
	F1 score	0.8388
BiLSTM	Accuracy	0.9050
	Precision	0.9071
	Recall	0.9050
	F1 score	0,9049
TCN	Accuracy	0.9150
	Precision	0.9150
	Recall	0.9200
	F1 score	0.9200
TCN-BiGRU	Accuracy	0.9520
	Precision	0,9600
	Recall	0.9500
	F1 score	0.9582
ALA-TCN-BiGRU-Attention	Accuracy	0.9800
	Precision	0.9752
	Recall	0.9752
	F1 score	0.9752

VI. CONCLUSIONS

This study puts forward a new deep learning method for the structural health monitoring of offshore jacket platforms. The primary benefit of the proposed method is rooted in its innovative integration of multiple neural network architectures. This integration enables the model to circumvent the limitations of individual architectures, thereby leveraging the strengths inherent in each architecture to accurately capture long-time sequence signals, emphasise the pivotal features of damage, and efficiently identify structural damage modes. The incorporation of the ALA enhances the model learning convergence speed and generalisation capability. Concurrently, the TCN can facilitate the extraction of long-time sequence signal features with enhanced efficiency. Additionally, the employment of the BiGRU provides a more comprehensive modelling of contextual information in time series sequences, which results in a significant enhancement of the modelling ability whilst maintaining a small parameter size in comparison to traditional unidirectional GRUs. As a result, the proposed ALA-TCN-BiGRU-attention model demonstrates a synergistic mechanism to enhance the defect identification accuracy in the structural health monitoring. The accuracy of damage identification is reported to exceed 98% in both finite element simulation and experimental evaluation, thus demonstrating high adaptability and robustness to diverse data sources of the proposed method. Moreover, the proposed method exhibits superior performance in comparison to traditional deep learning methods, characterised by accelerated convergence, enhanced stability and elevated accuracy. This approach has been demonstrated to provide a powerful and versatile solution for damage detection on offshore platforms. Next step will evaluate the proposed method using field data.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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